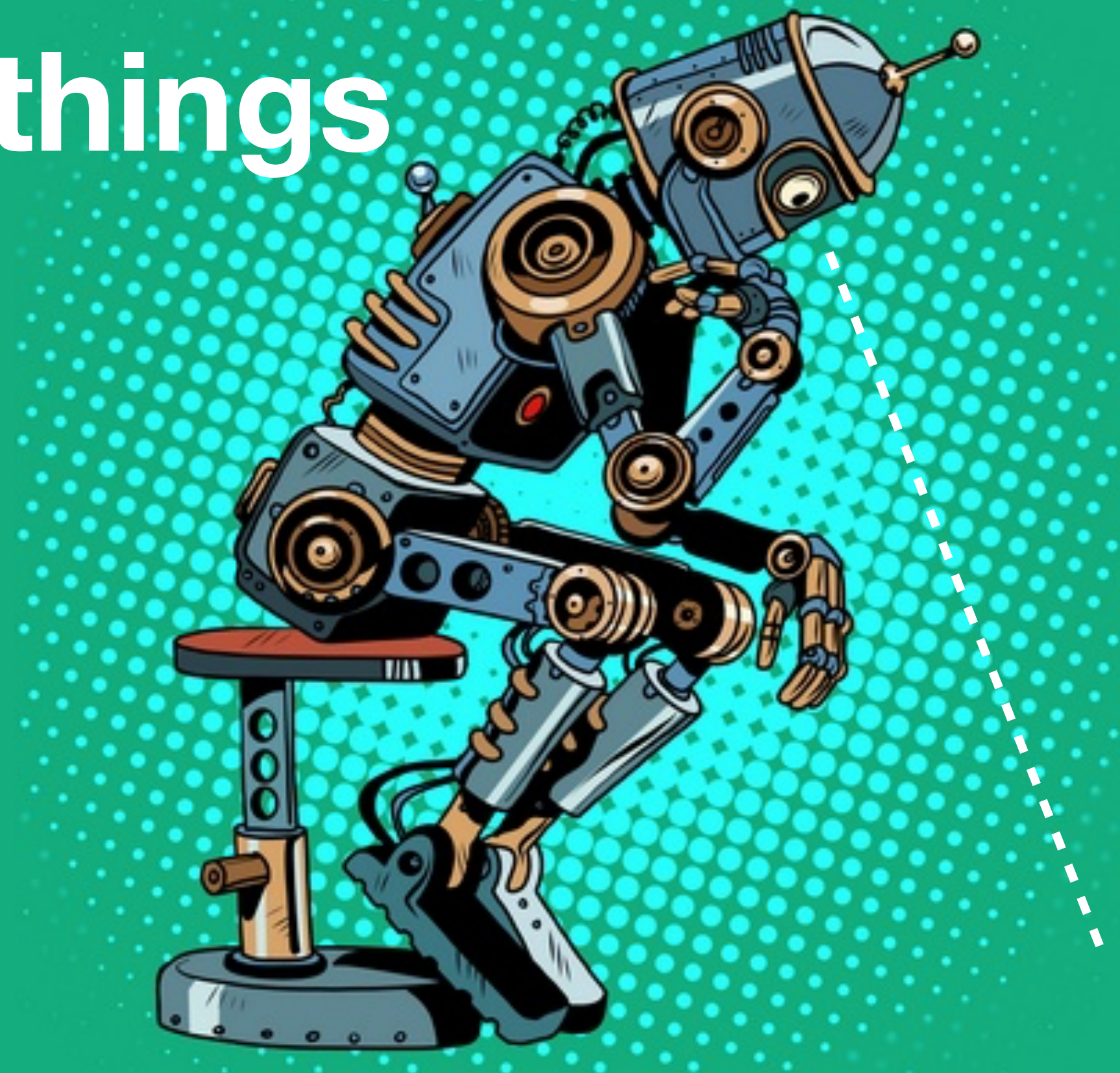
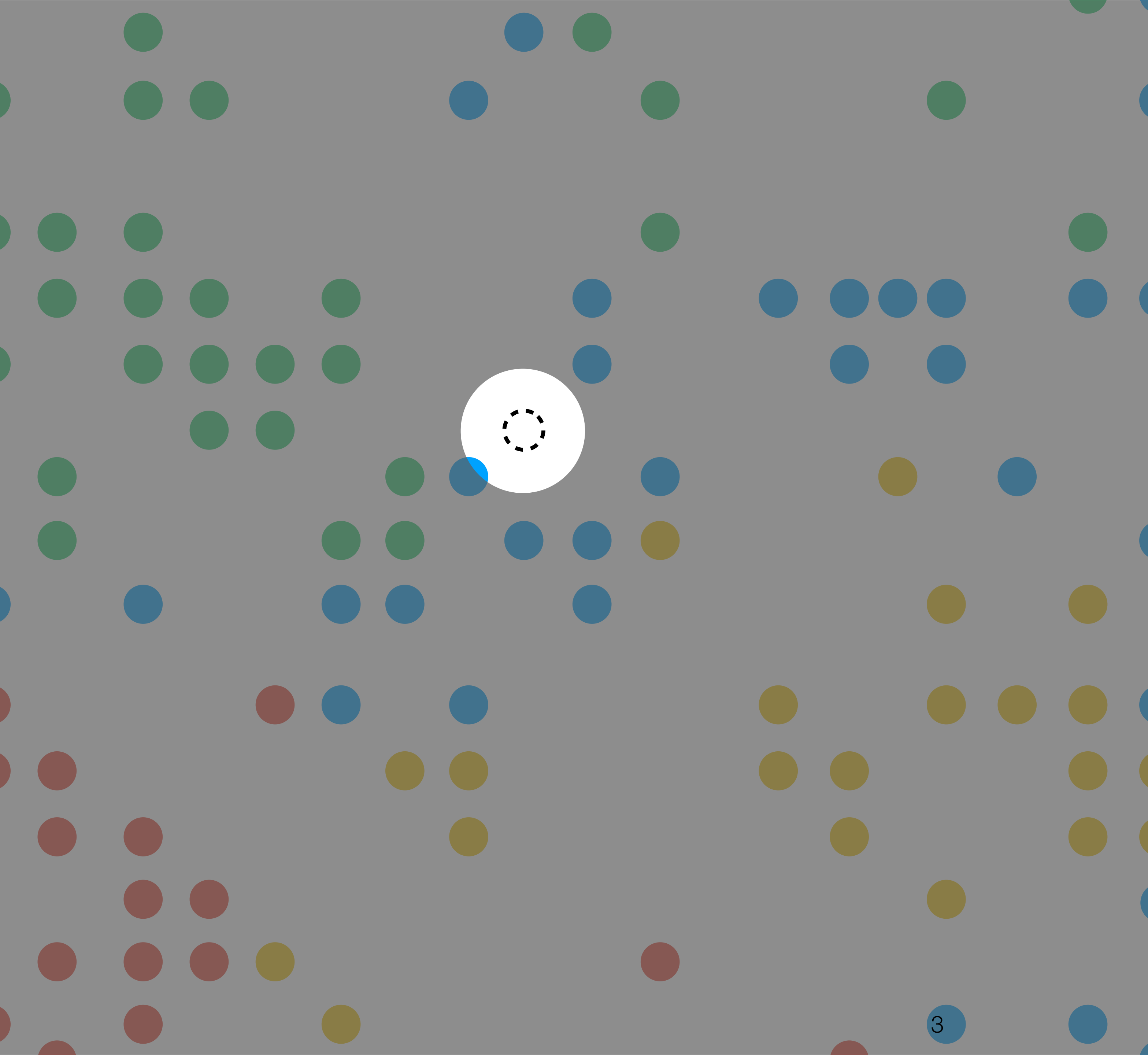


# How does the machine Learn the new things from data?



C.S Wang  
2019. 07. 18

# K Nearest Neighbor



## ■ K Nearest Neighbor

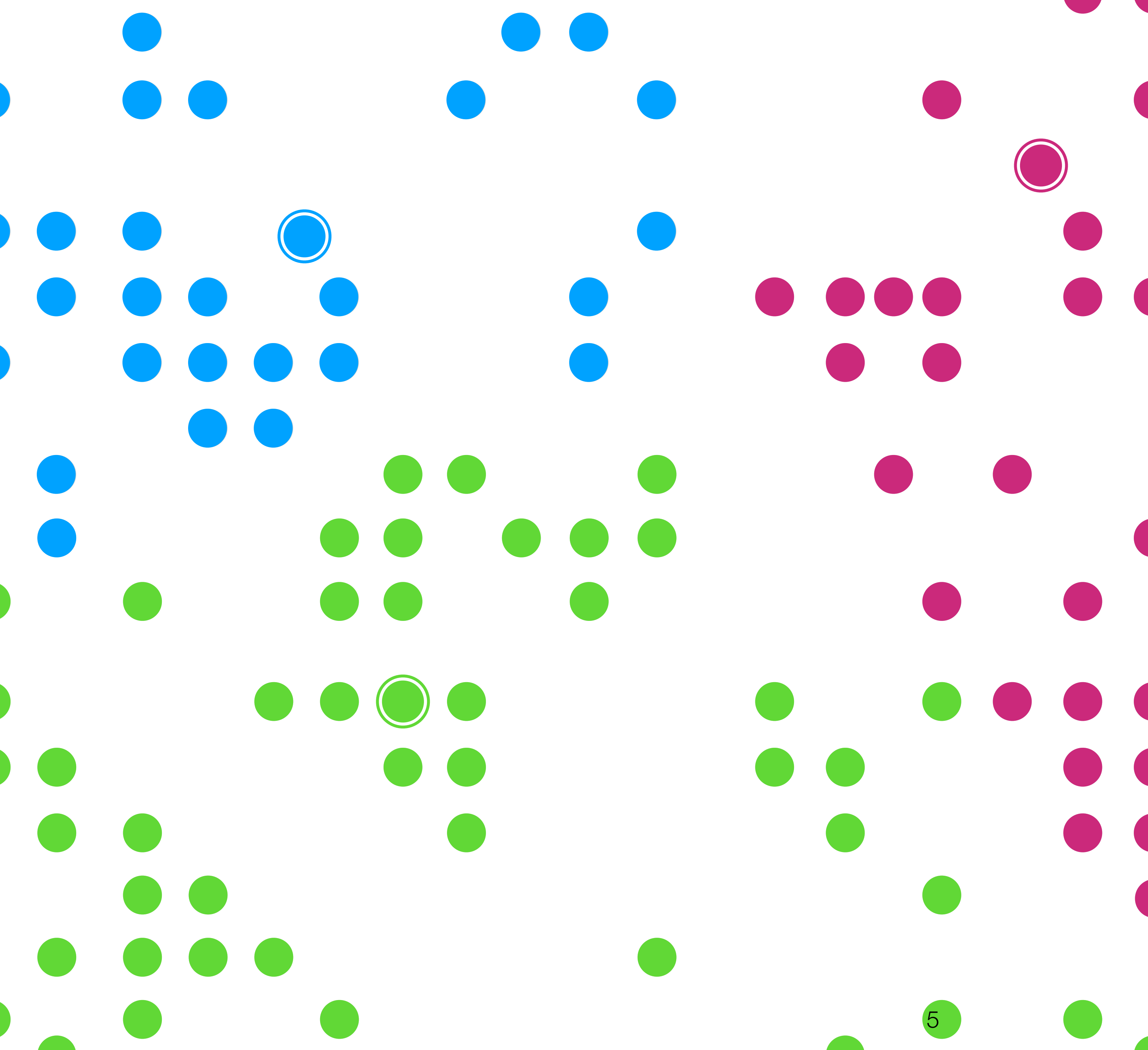
- K is the **Parameter**

- Depend on Top-K neighbors  
**Ensemble**

- **Distance Calculation**

ex: Euclidean distance

# K-Means



## ■ K Means

without Label

■ K is number of clusters

■ Clustering the data together

■ Distance Calculation

ex: Euclidean distance



# Naive Bayes

$$\text{Posterior} = \frac{\text{Likelihood} \text{ Prior}}{\text{Evidence}}$$
$$P(y | x) = \frac{P(x | y)P(y)}{P(x)}$$

## ■ Before we start...

Some things you should know. One of most important thing is **creating a table** for your data.



## Basic things

### Step by Step




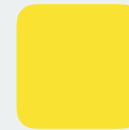
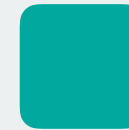
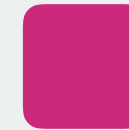
#### Prior

+

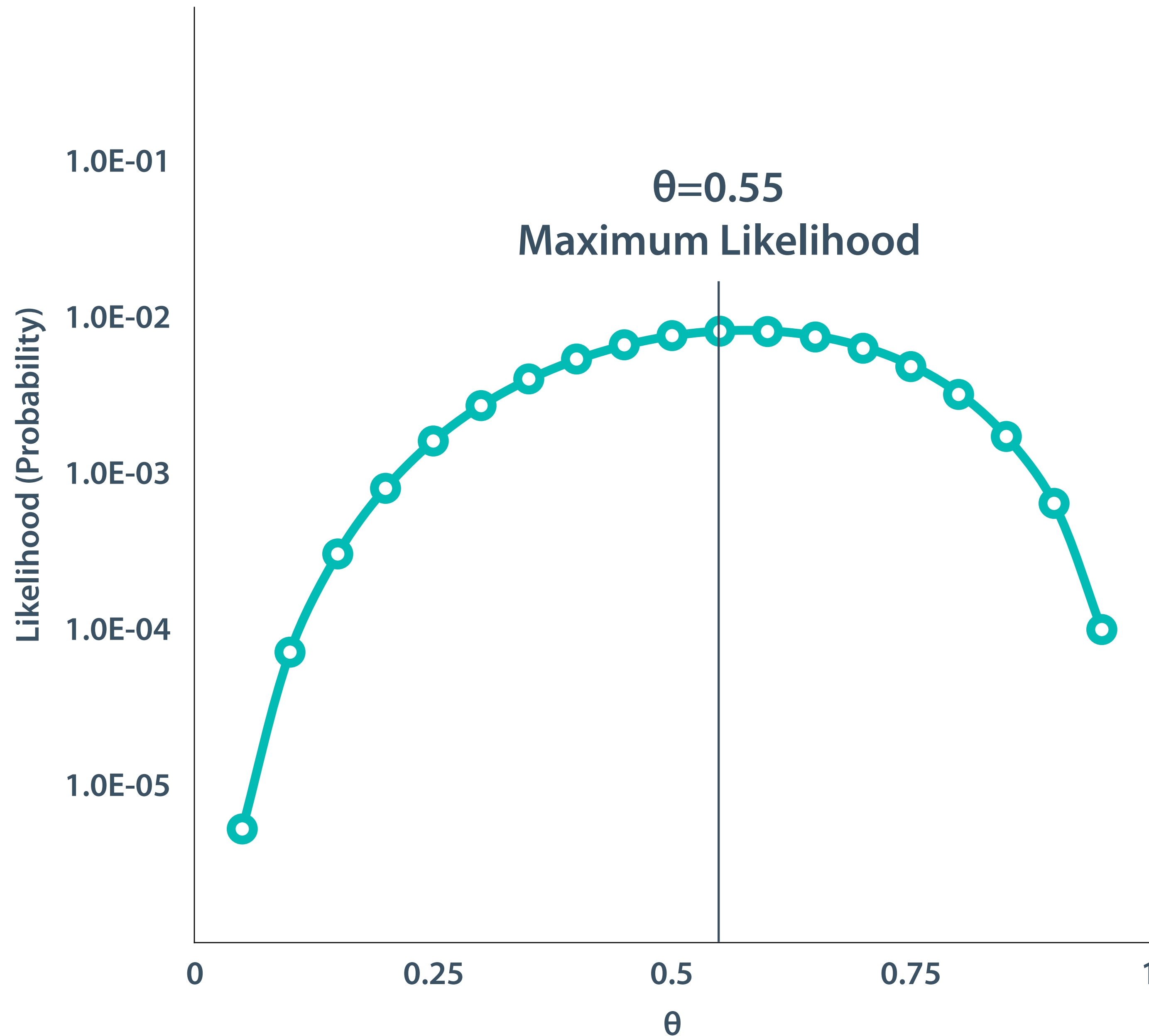
-

390/1000 610/1000

#### Likelihood

						
+	$\frac{50}{150}$	$\frac{70}{230}$	$\frac{250}{500}$	$\frac{190}{191}$	$\frac{250}{660}$	$\frac{270}{530}$
-	$\frac{100}{150}$	$\frac{160}{230}$	$\frac{250}{500}$	$\frac{1}{191}$	$\frac{410}{660}$	$\frac{260}{530}$





## ■ Likelihood

Informal, as a synonym for  
**probability**

■ **How well** the data summarizes  
these **parameter  $\theta$**

■ It represented by  $L(\theta|x)$

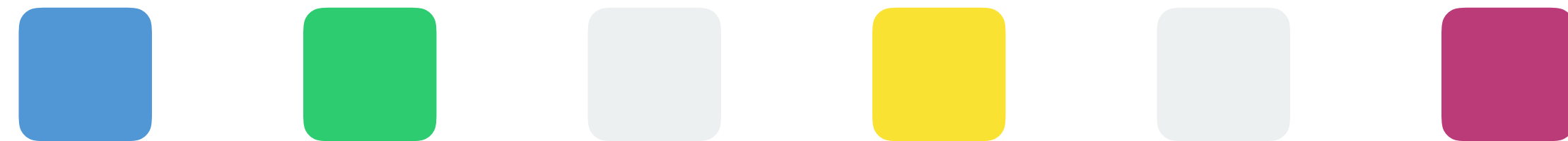
$$L(\theta|x) = P(x|\theta)$$

## ■ Toy Example

Observed Data: HHTHTTH

What is  $\theta$  ?

How to estimated it?



+(Positive) or -(Negative)?

## Naive Bayes


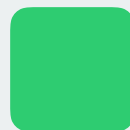
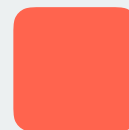

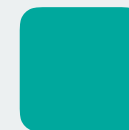
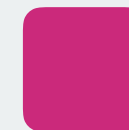
### Inference

$$P(y | x) = \frac{P(x | y)P(y)}{P(x)}$$

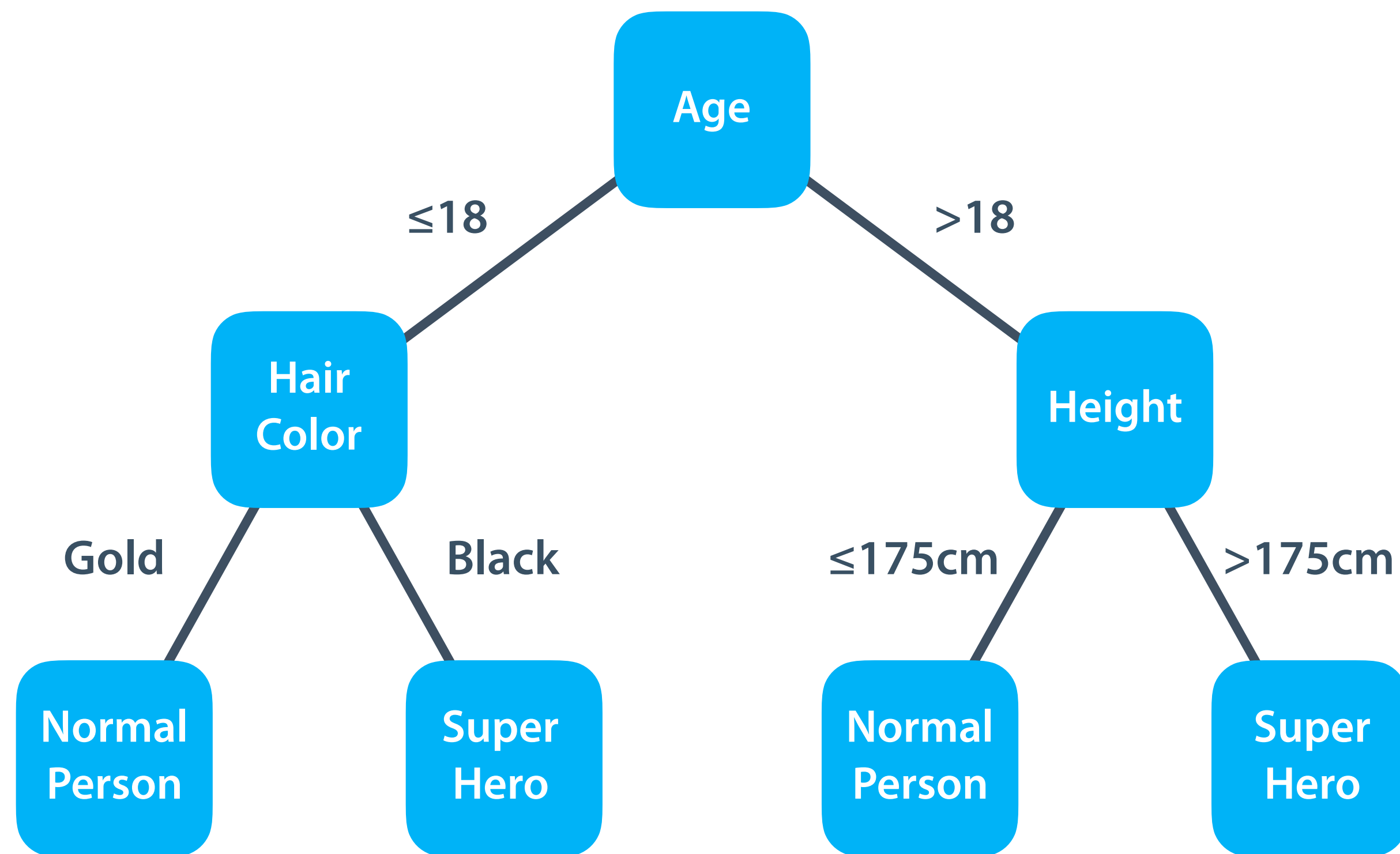
### Prior

+	-
390/1000	610/1000

### Likelihood

						
+	$\frac{50}{150}$	$\frac{70}{230}$	$\frac{250}{500}$	$\frac{190}{191}$	$\frac{250}{660}$	$\frac{270}{530}$
-	$\frac{100}{150}$	$\frac{160}{230}$	$\frac{250}{500}$	$\frac{1}{191}$	$\frac{410}{660}$	$\frac{260}{530}$

# Decision Tree



## ■ Decision Tree

To see how to make a decision

- First, the **data** should be **discrete**

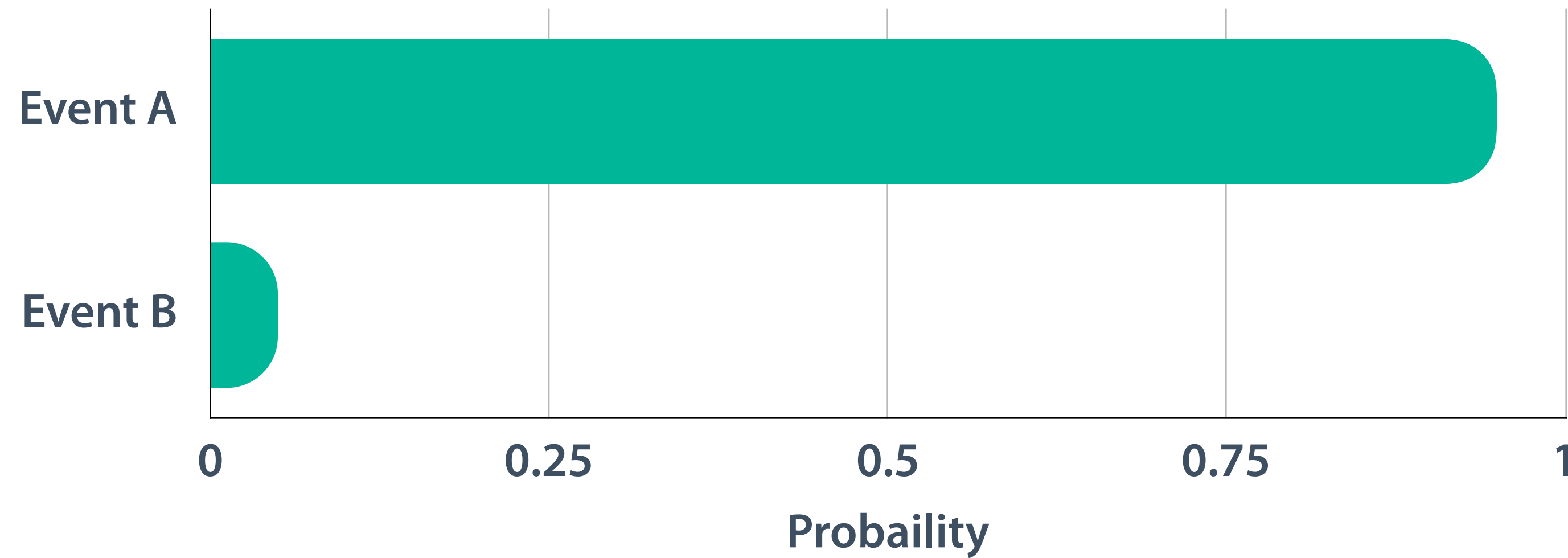
Transforming it, if it was continuous

- How to find the **suitable node** to split it?

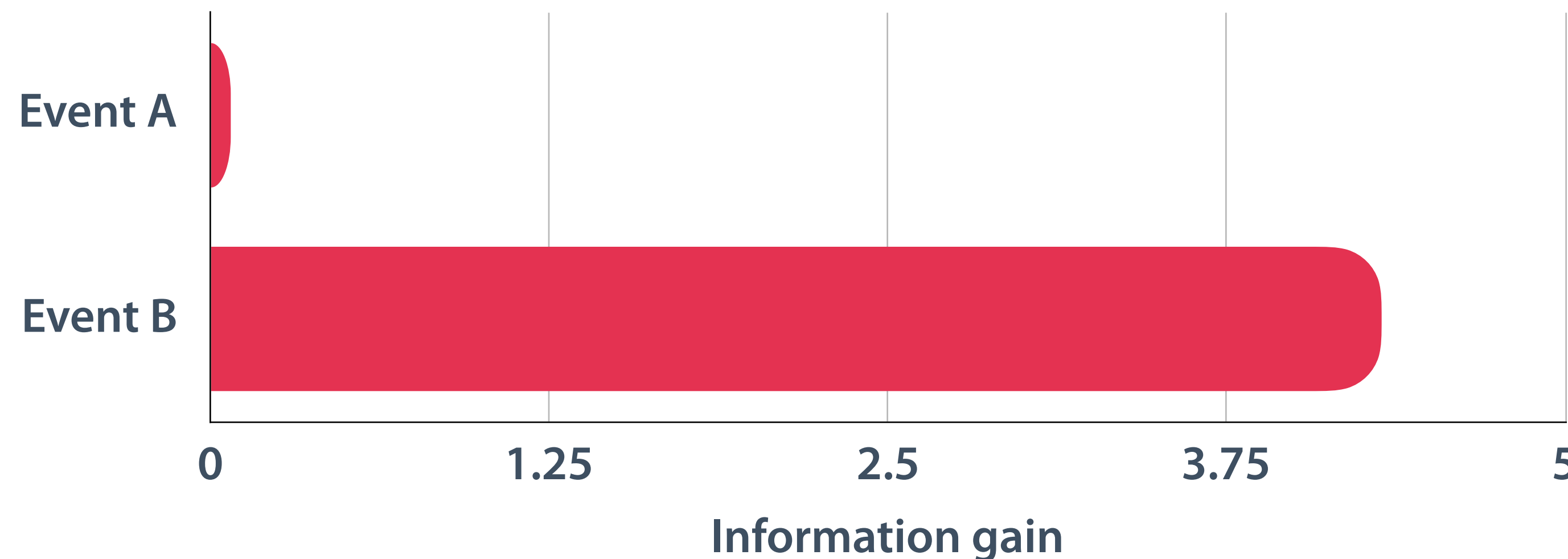
Information gain & Entropy

- Basic idea! **Information**

Probability of event occurred



Information gain for event



## Information Gain

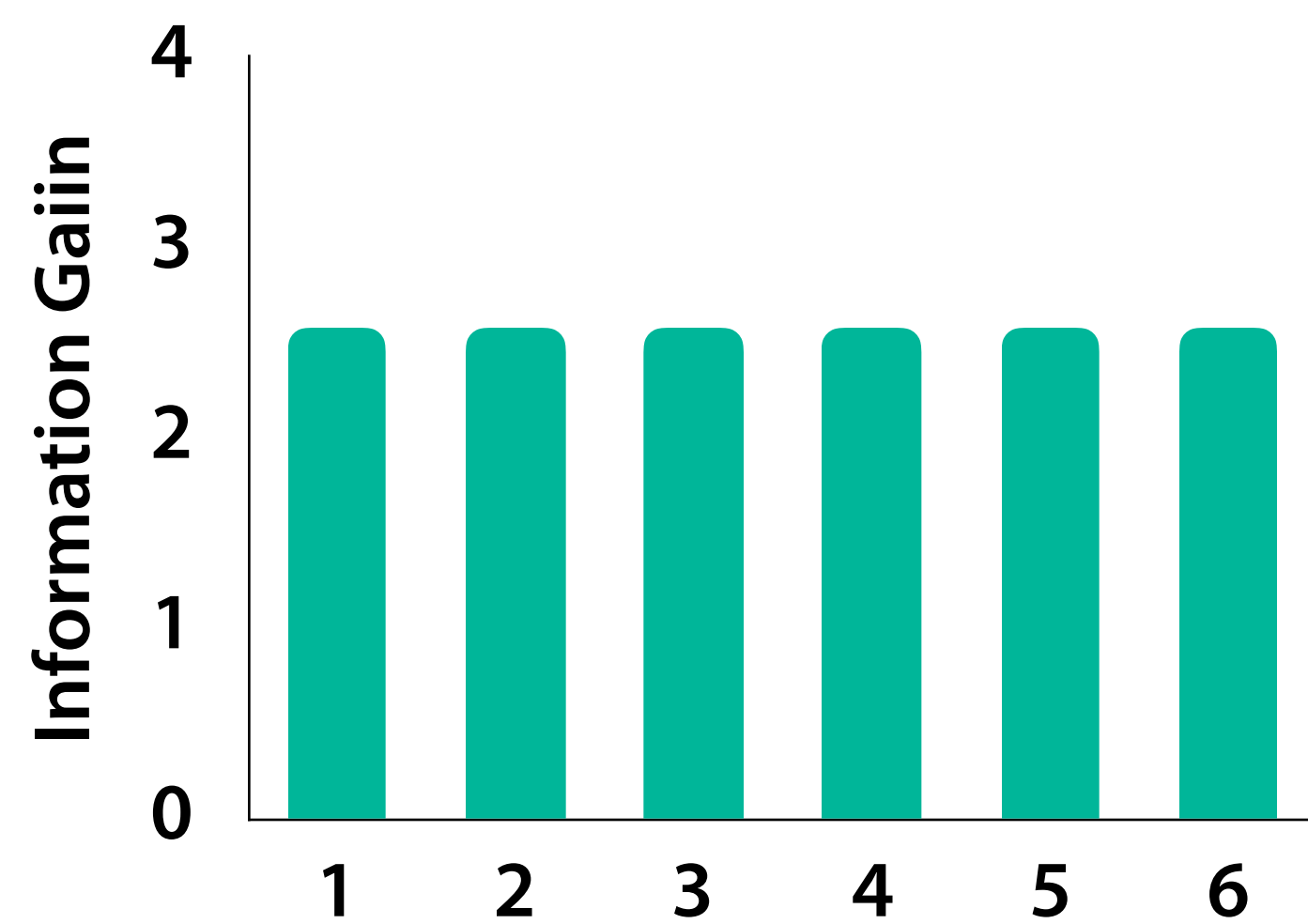
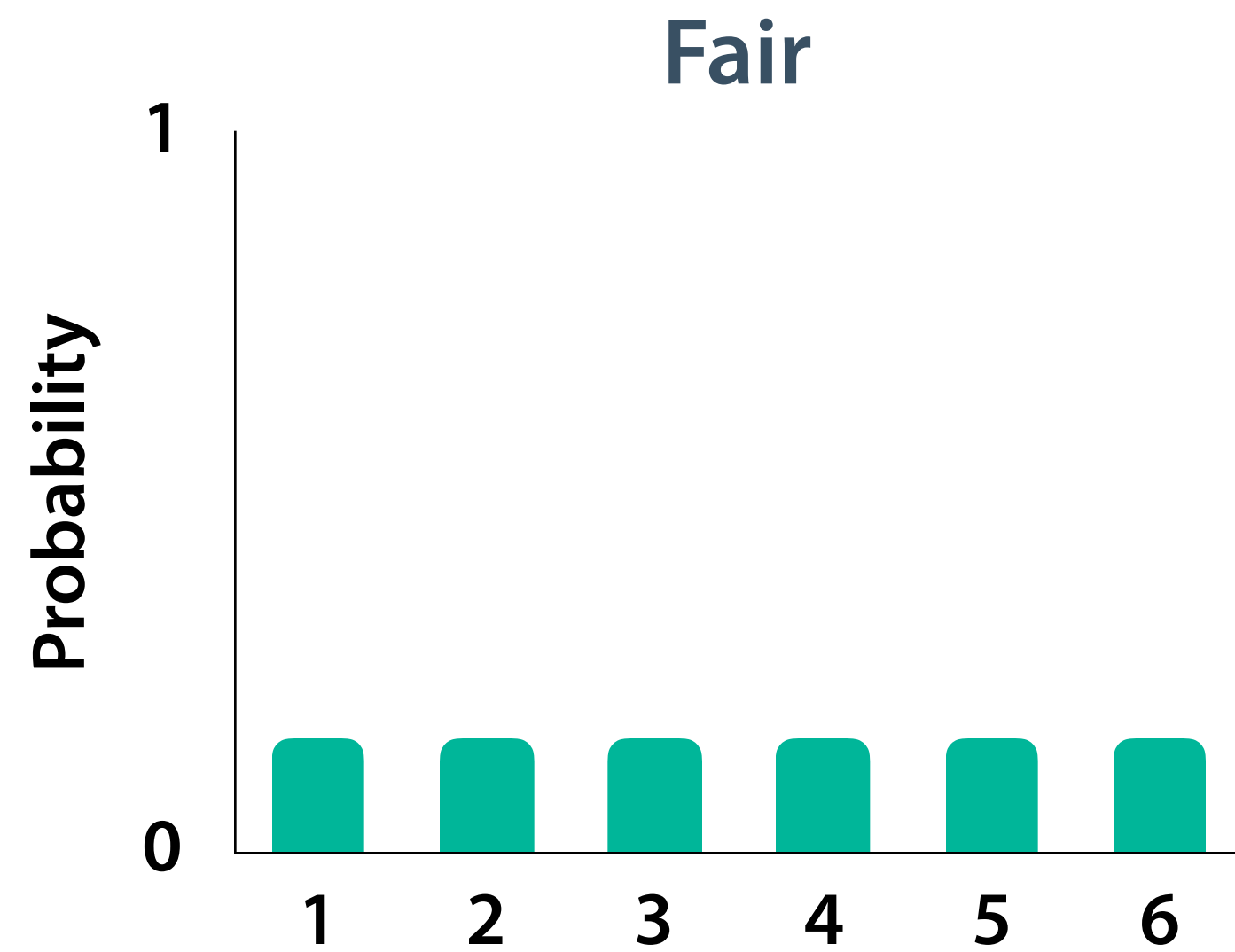
Evaluated your information

### Which is more important?

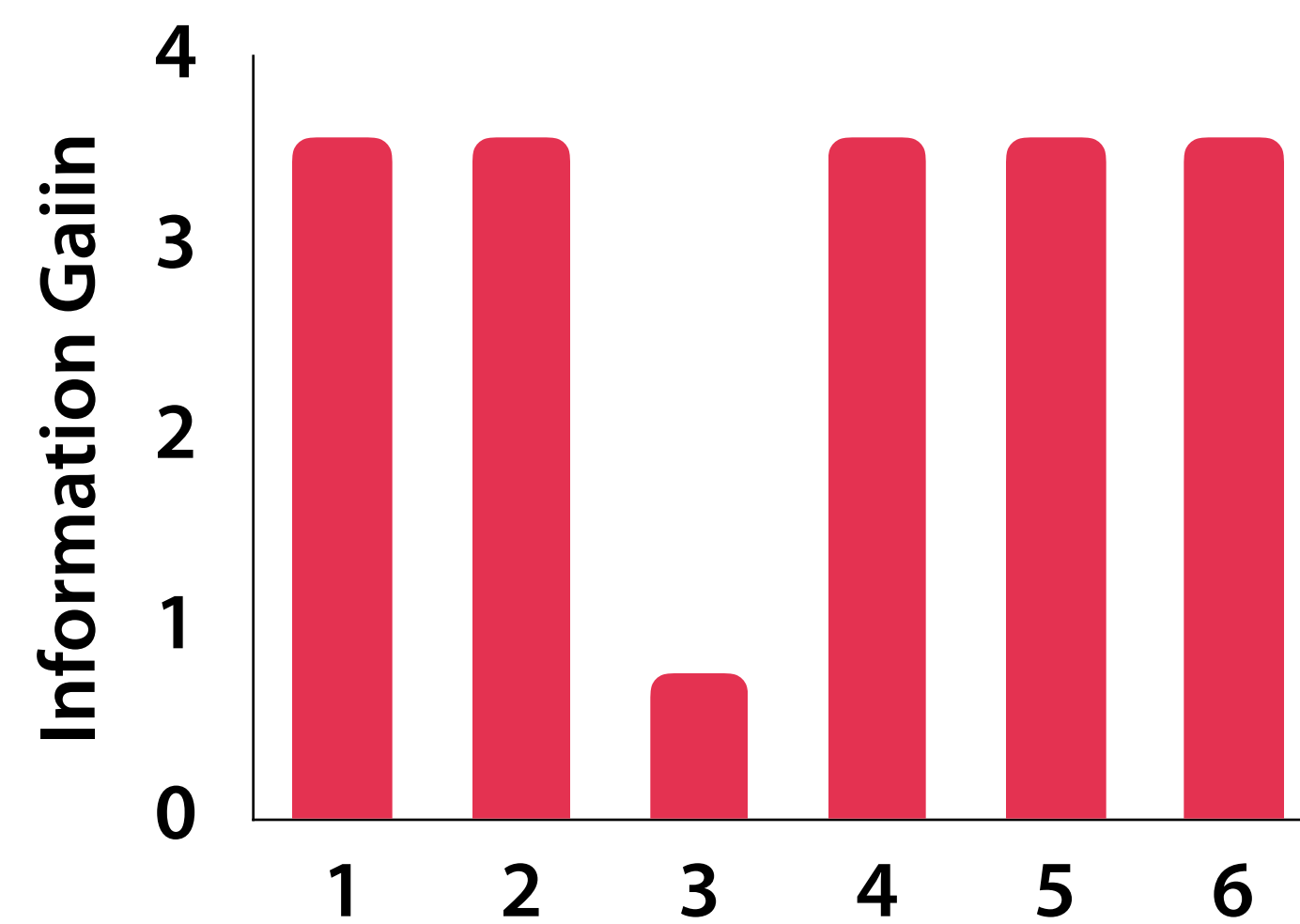
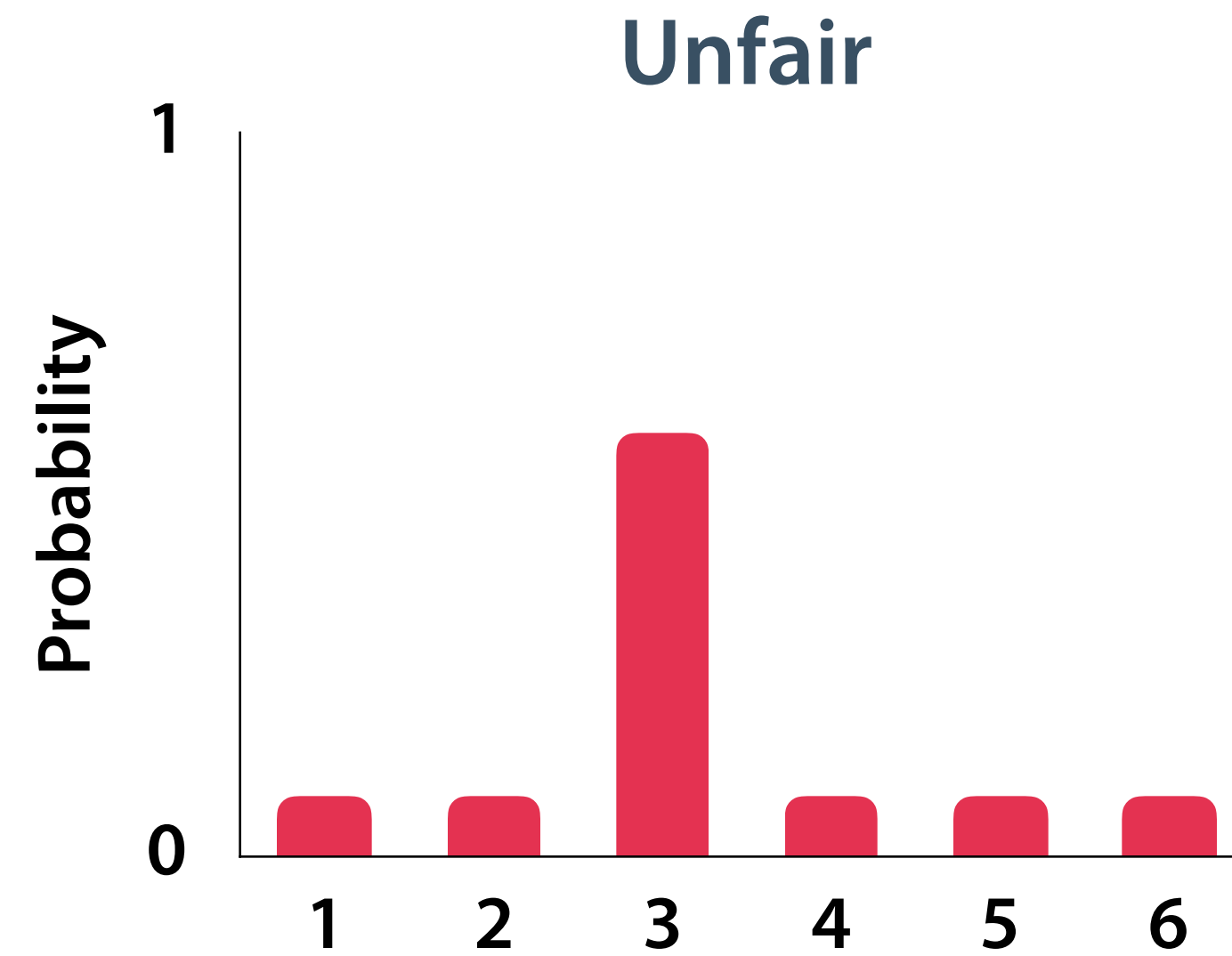
Event A has 95% to occur  
Event B has 5% to occur

### (Shannon) Information Gain

$$IG(E) = -\log P(E)$$



$$H(X) = 2.585$$



$$H(X) = 1.94$$

## Entropy

Information overall **uncertainty**

■ Expectation of information gain

$$H(X) = - \sum_{i=1}^n P(x_i) \log P(x_i)$$

■ Fair dice vs unfair dice

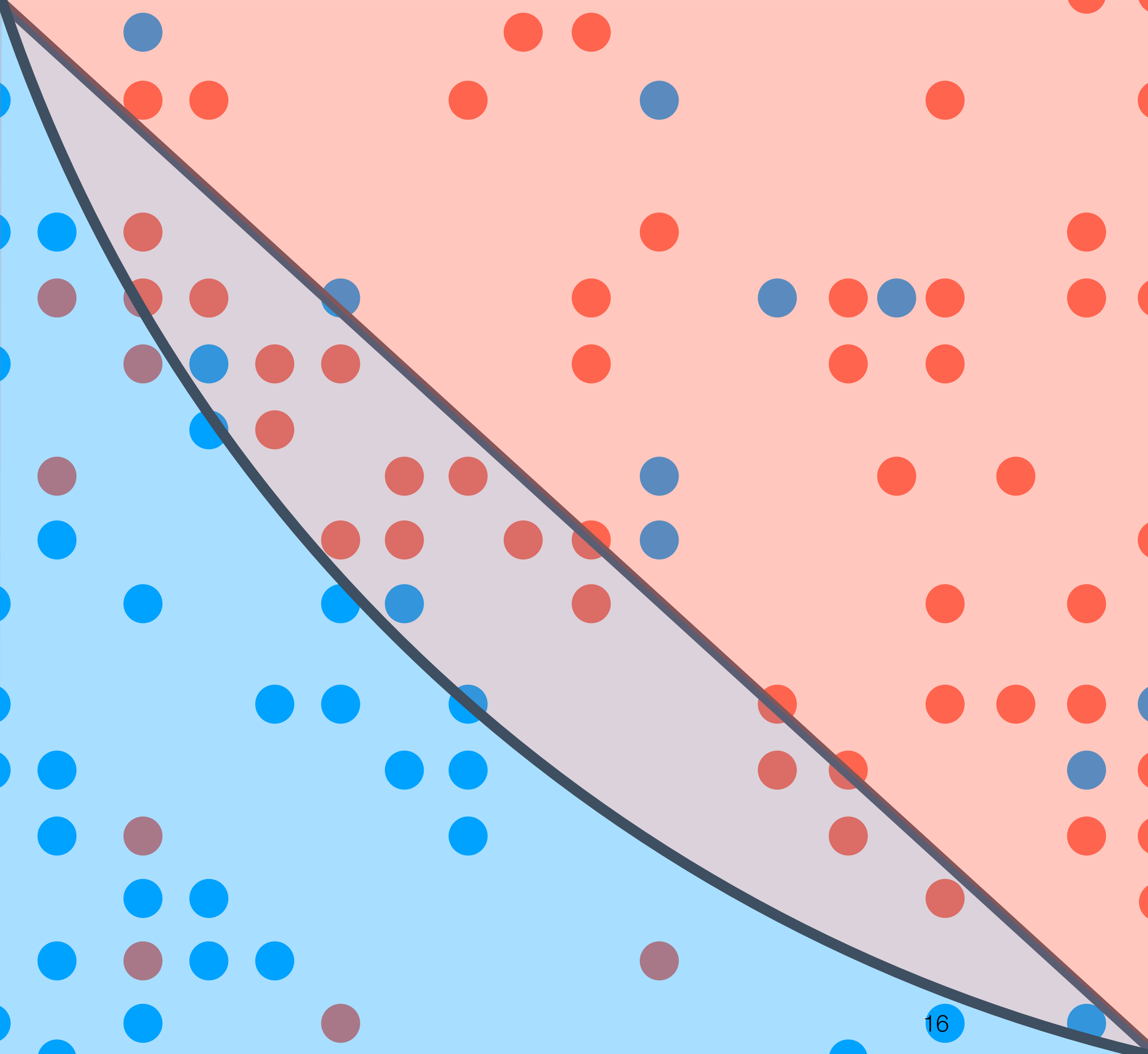
	1	2	3	4	5	6
Fair	1/6	1/6	1/6	1/6	1/6	1/6
Unfair	1/12	1/12	7/12	1/12	1/12	1/12

■ Does large value means better?

**Noooooo!! it's more uncertainty**

# Logistic Regression





## ■ Logistic Regression

The significance of **weight**

- How to **split** these data into two parts?

Assume this is a binary classifier

- **Logistic Function**

$$h(x) = \frac{1}{1 + e^{-W^T X}}$$

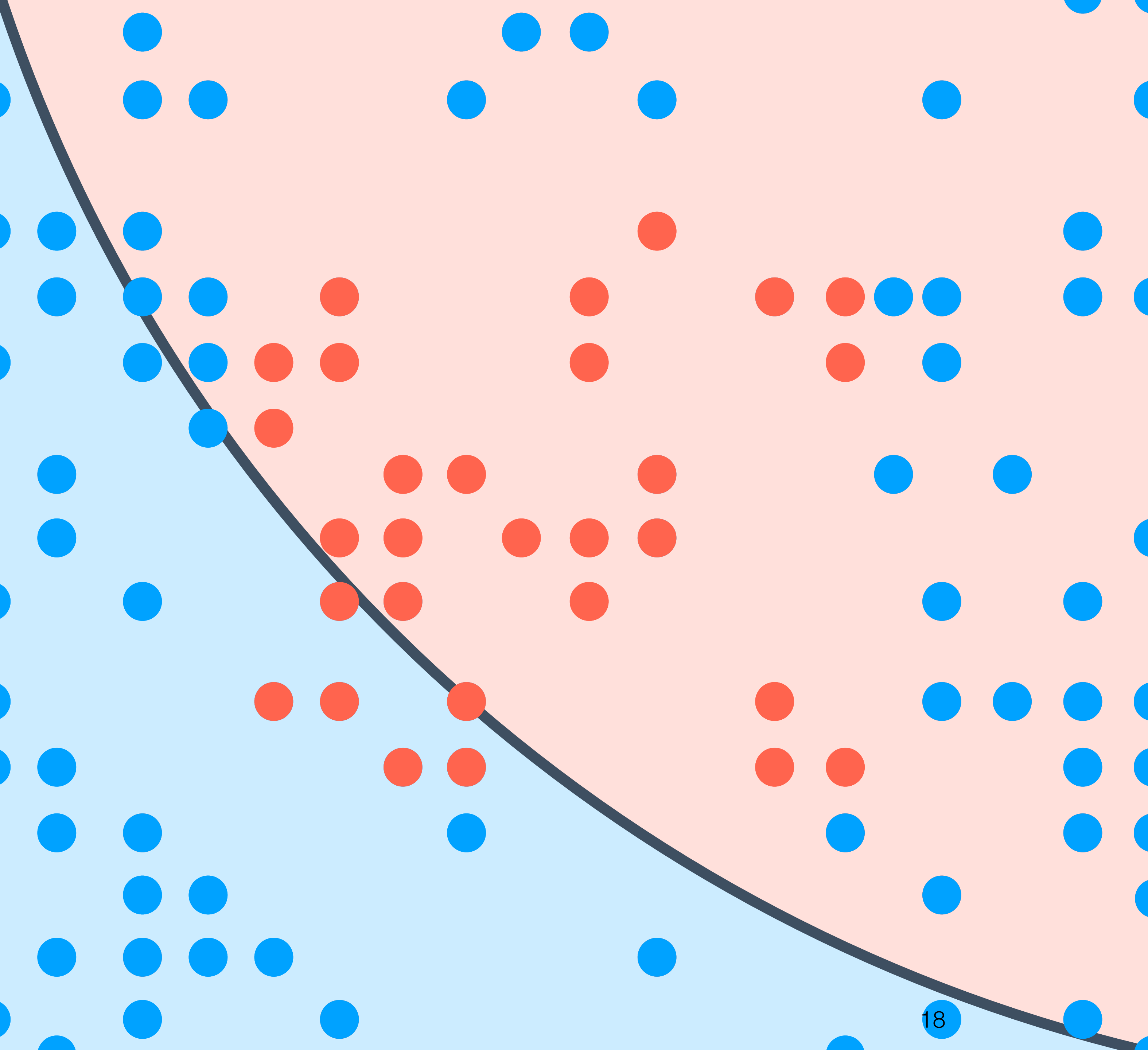
- **Weight update**

Gradient descent

- How about **linear regression**?

$$h(x) = W^T X + b$$

# Support Vector Machine



# ■ Support Vector Machine

Going into high dimension space

■ Why we need this?  
(Don't forget logistic regression)

■ Support Vector & Support Plane

■ How to calculate the **similarity** in  
high dimension space?

Using **Kernel Function**  
**ex: linear, Polynomial, RBF**